Soil moisture active-passive (SMAP) mission data for hillslope-scale soil moisture estimation with a spatially distributed ecohydrology model and data assimilation

Alejandro N. Flores[1], Dara Entekhabi[1], and Rafael L. Bras[2]

1 – Department of Civil and Environmental Engineering, Massachusetts Institute of Technology, Cambridge, MA
2 – Henry Samueli School of Engineering, University of California, Irvine, CA

1. PROBLEM STATEMENT

NASA's Soil Moisture Active-Passive (SMAP) mission seeks to provide both active (radar) and passive (radiometer) data in the L-band microwave region of the spectrum. L-band microwave observations of the surface are sensitive to the amount of near-surface moisture in the soil.

Accurate knowledge of the spatial distribution of soil moisture at **hillslope scales** (e.g., 10's to 100's of meters) can significantly advance applications requiring high-resolution soil moisture information. The spatial distribution of soil moisture is controlled across a range of scales by variability in topography, soils, vegetation, and precipitation.

Although the ground resolution of the proposed SMAP products is too coarse to capture hillslope-scale variation in soil moisture, they are nevertheless **useful for hillslope-scale estimation in the context of a data assimilation system**. Here we describe efforts to construct an ensemble Kalman Filter to fuse simulated noisy L-band microwave brightness and radar backscatter observations with uncertain hillslope scale soil moisture estimates derived from a physically-based ecohydrology model.

2. EXPERIMENTAL DESCRIPTION

The purpose of this experiment is to **demonstrate that SMAP L-band micro-wave radar backscatter observations are valuable for hillslope-scale soil moisture**, through a data assimilation framework that combines noisy L-band microwave observations with hillslope-scale estimates of moisture from a process hydrology model.

The lack of space-borne L-band observations necessitates an Observing System Synthetic Experiment (OSSE) approach to evaluate the potential.

In this synthetic experiment we use the Integral Equation Model (IEM) to simulate radar backscatter observations assuming the following:

> Observations occur every 72 hours at 0900 local time
> Radar instrument consistent with SMAP specifications (1.26 GHz)
> Radar backscatter products have a ground resolution of 3 km

Fig 1: Location of Walnut Gulch experimental watershed in Arizona, USA.

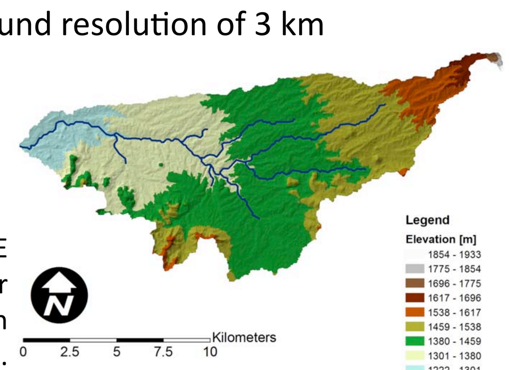


Fig 2: tRIBS-VEGGIE computational mesh for Walnut Gulch watershed.

The semiarid Walnut Gulch Experimental Watershed (WGEW) in Arizona, USA is used as the experimental setting.

The ecohydrology model used here is the Triangulated Irregular Network (TIN)-based Realtime Integrated Basin Simulator and Vegetation Integrated Evolution model (tRIBS-VEGGIE) [*Ivanov*, 2008a].

tRIBS-VEGGIE resolves moisture, energy, and carbon balance. Infiltration is simulated via the 1-D Richards equation with moisture redistribution in the vadose zone occurring in the steepest, downslope direction. The WGEW computational mesh contains 19,447 pixels with 10 soil layers.

3. ACTIVE OBSERVING SYSTEM

The **Integral Equation Model (IEM)** is used as the observing system to simulate backscattered L-band microwave energy based on the near-surface moisture content.

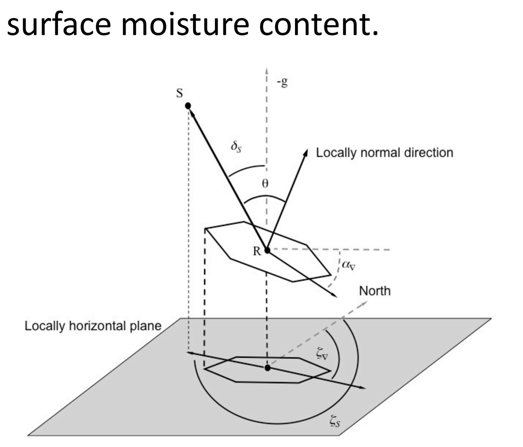


Fig 3: Schematic representation of the impact of slope and aspect on observational geometry

The observing system explicitly treats the influence of topography on the observational geometry.

Local incidence and polarization rotation angles are determined by the **topographic slope** and **aspect**, as well as satellite sky position as parameterized by an **azimuth and zenith angle.**

The observing system is used to simulate backscatter observations every 72 hours based on four potentially true evolutions of the soil moisture field simulated by tRIBS-VEGGIE and aggregated to a scale of 3 km.

At each analysis, the observing system is used to produce predicted observations

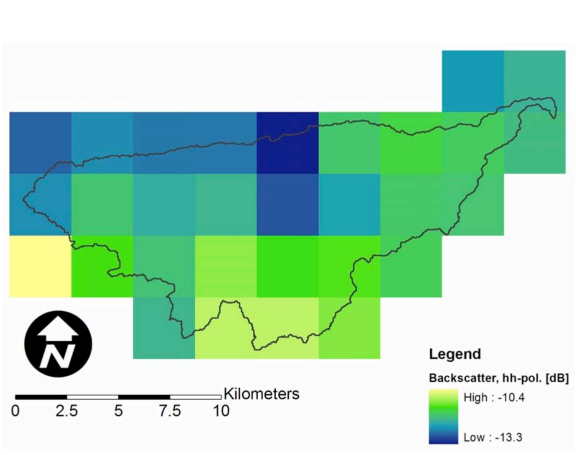


Fig 4: Average of four observations simulated from four true states in the horizontally-copolarized state at 216 hr.

4. SOURCES OF UNCERTAINTY

The primary assumed sources of uncertainty in soil moisture predictions are: (1) **uncertainty in the hydrometeorological forcings** supplied to the model, and (2) **inadequate knowledge of soil hydraulic and thermal properties** in the watershed.

The spatial organization of soil textural classes is assumed known. Soil parameters are generated using a **Latin Hyper-cube based approach that preserves correlation among parameters** for each soil textural unit.

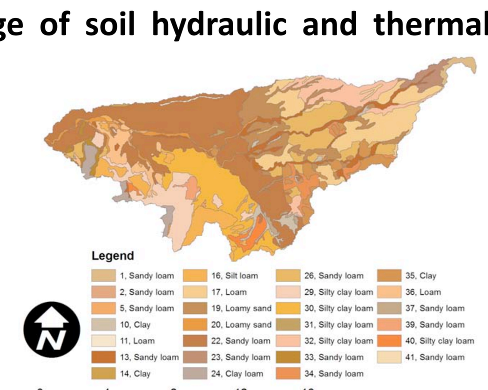


Fig 5: The distribution of soil types in WGEW.

4. SOURCES OF UNCERTAINTY

Ensembles of **hydrometeorological forcings are simulated with three simple stochastic models**: (1) a stochastic model of hourly rainfall, (2) a cascade model to perturb hourly rainfall rates and disaggregated hourly rainfall in space, and (3) a **weather generator** to simulate thermodynamic weather forcings [*Ivanov*, 2008b]

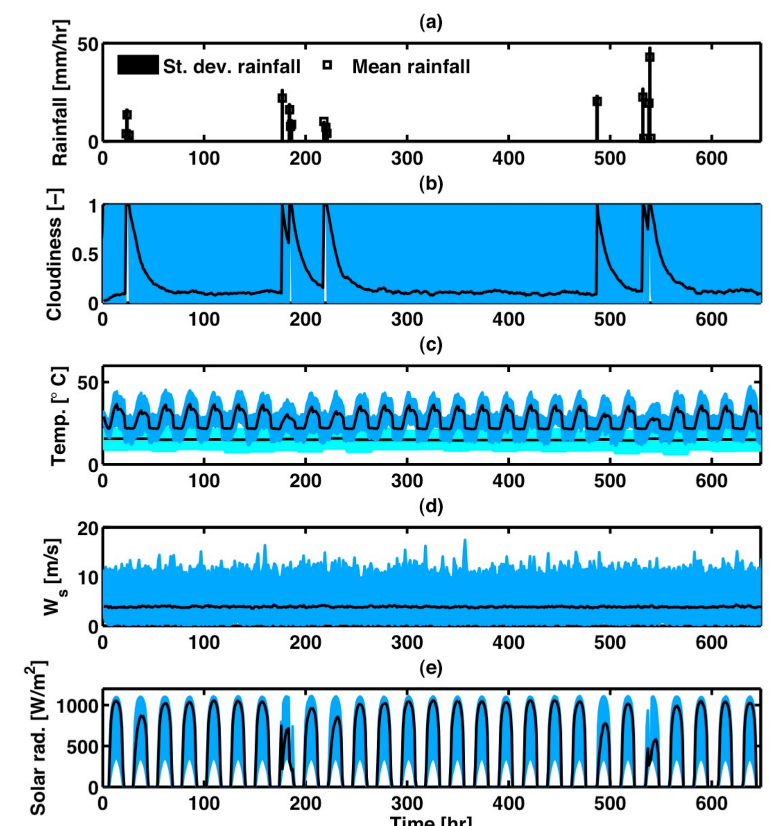


Fig 6: A summary of the stochastic hydrometeorological forcings used in the experiment.

5. DATA ASSIMILATION APPROACH

A **square root analysis ensemble Kalman Filter (EnKF)** [*Evensen* 2004] updates the tRIBS-VEGGIE simulated soil moisture state based on 256 replicates. tRIBS-VEGGIE is re-initialized with analyzed states, which are propagated forward to the next analysis, influenced by uncertain forcings and parameters. Nine forecast-analysis cycles are performed (27 days).

The **EnKF experiment is repeated with four sets of observations simulated from four potentially true realizations of soil moisture**, and results are compared against a 1024 replicate open loop ensemble.

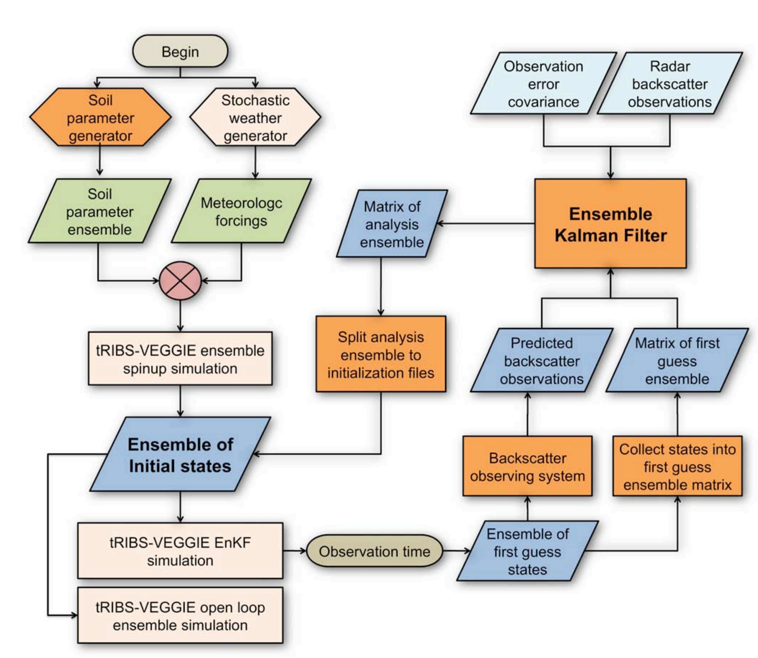


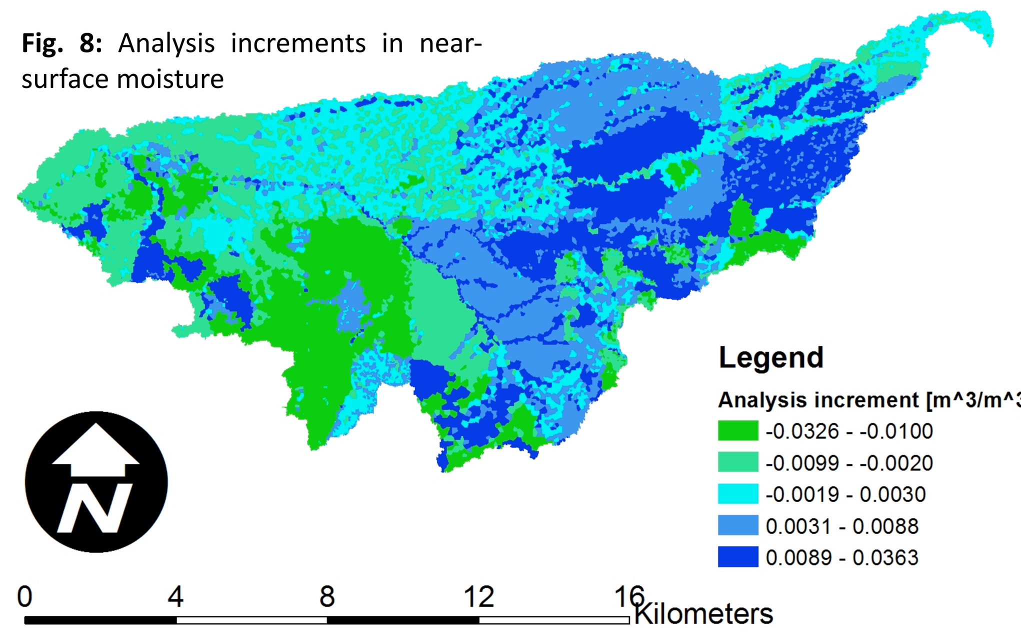
Fig 7: A flowchart of the EnKF-based hillslope-scale moisture estimation experiment

6. RESULTS: ANALYSIS INCREMENTS

Analysis increments averaged across the four experiments exhibit spatial structure associated with heterogeneity in soil types and topography.

The **square structures seen also suggest that the EnKF may be effectively correcting errors in precipitation.**

Fig. 8: Analysis increments in near-surface moisture

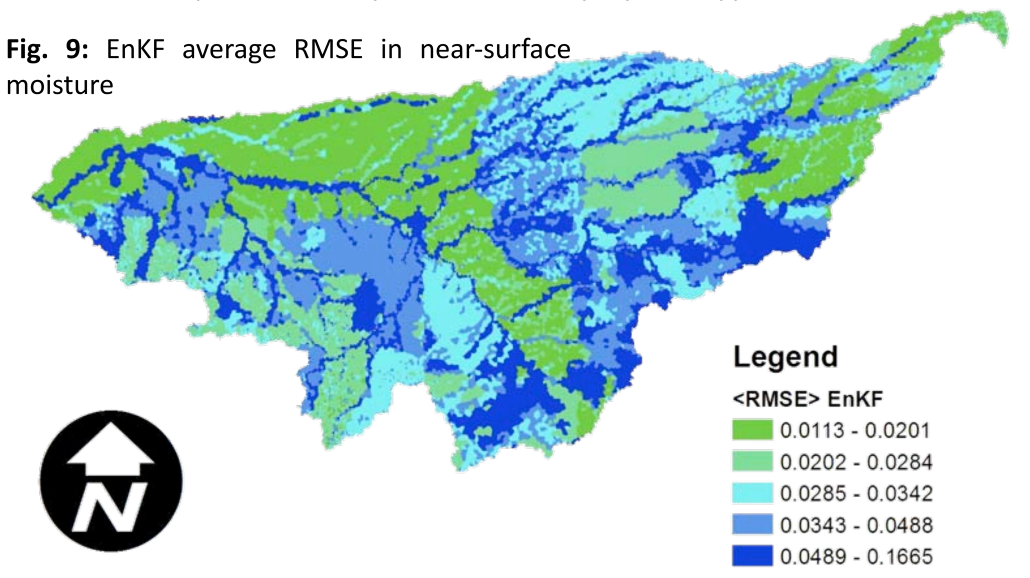


RMSE values averaged across experiments suggest **relatively low estimation error in predictions of near-surface soil moisture.**

The channel network seems to be associated with higher average RMS error in near-surface soil moisture.

Furthermore, predictability seems to vary by soil type

Fig. 9: EnKF average RMSE in near-surface moisture

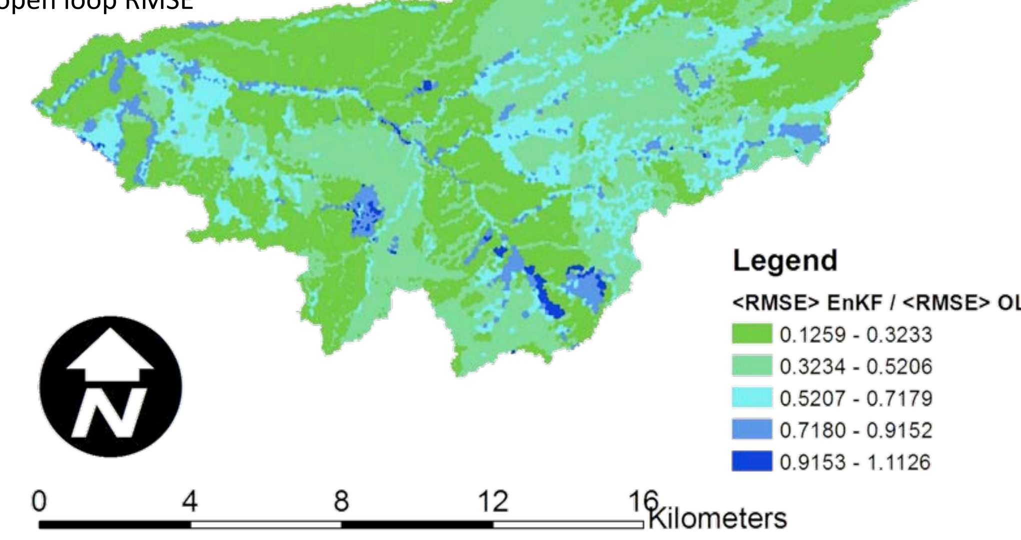


6. RESULTS (CONT.): ERROR REDUCTION

Relative to a 1024 replicate open loop simulation, the **error in the EnKF estimate of near-surface moisture is substantially lower in the majority of the watershed.**

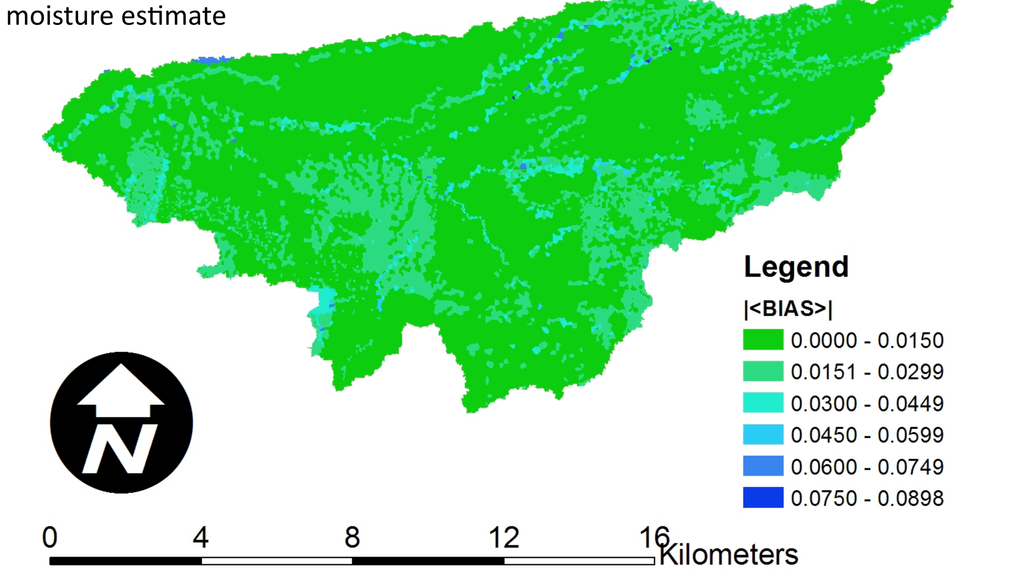
The figure suggests that in much of the WGEW, the average **RMS errors in the EnKF prediction of near surface moisture are less than 53% of the corresponding RMS errors in the open loop prediction.**

Fig. 10: Comparison of EnKF and open loop RMSE



The **bias associated with the EnKF estimate of near surface soil moisture is also relatively small.**

Fig. 11: Average bias in near-surface moisture estimate



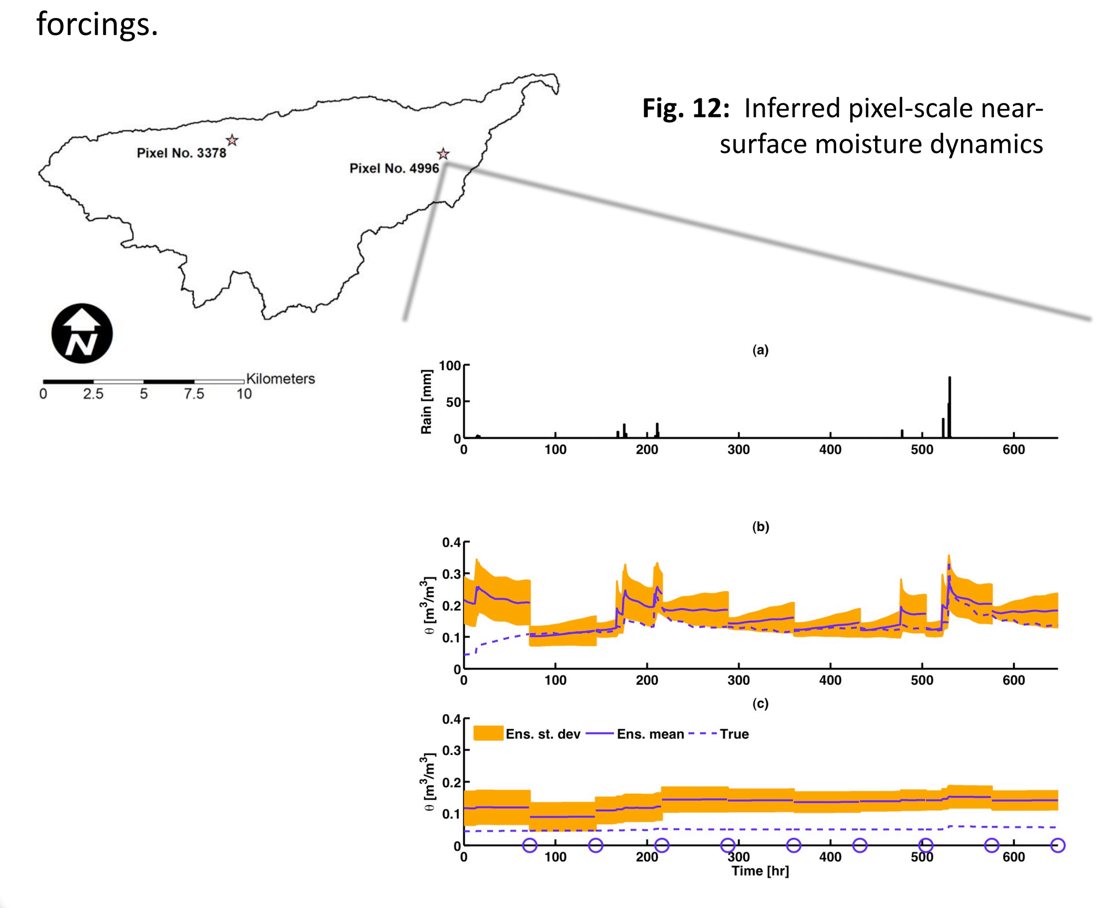
6. RESULTS (CONT.): MOISTURE DYNAMICS AT THE PIXEL SCALE

Temporal dynamics of near-surface and profile-integrated moisture content during the EnKF experiment are investigated at two pixels within WGEW (shown for one set of observations below).

Results show that the **EnKF dramatically improves the pixel scale estimate of the near-surface soil moisture at the analysis**. However, the estimate of profile moisture does not converge to the truth during the experiment.

However, the pixel scale estimate diverges from the true moisture dynamics relatively rapidly, owing to uncertainty in the parameters and forcings.

Fig. 12: Inferred pixel-scale near-surface moisture dynamics



7. SUMMARY

This work demonstrates the **potential importance of SMAP observations for improving soil moisture knowledge at hillslope-**scales, thereby potentially benefitting applications requiring information in such high detail.

Success of the assimilation approach is preconditioned, however, on adequate representation of uncertainty in forcings and parameters and an observing system to simulate observations based on model states.

Accurate estimation of profile-integrated moisture content may require a longer assimilation experiment, larger ensembles, or better constraints on parameter values.

REFERENCES

Evensen, G., "Sampling strategies and square root analysis schemes for the EnKF," *Ocean Dynam.*, vol. 54, pp. 539-560, 2004.
Ivanov, V. Y., R. L. Bras, and E. R. Vivoni, "Vegetation-hydrology dynamics in complex terrain of semi-arid areas: 1. A mechanistic approach to modeling dynamic feedbacks," *Water Resour. Res.*, vol. 44, doi: 10.1029/2006WR005588, 2008a.
Ivanov, V.Y., R. L. Bras, and D. C. Curtis, "A weather generator for hydrological, ecological, and agricultural applications," *Water Resour. Res.*, vol. 43, doi: 10.1029/2006WR005364, Oct. 2007.

This work was supported by Army Research Office grant no. W911NF-04-1-0119